Investigation on Optimal Mixing with Linkage Sets and Its Application

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Outline

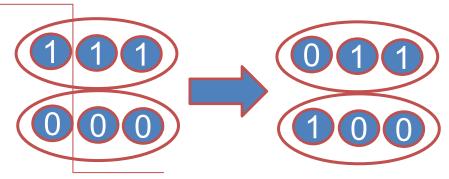
- 1. Background Knowledge
- 2. Motivation
- 3. Investigation on Different Masks
- 4. Optimal Mixing with Mask Selection
- 5. Conclusion

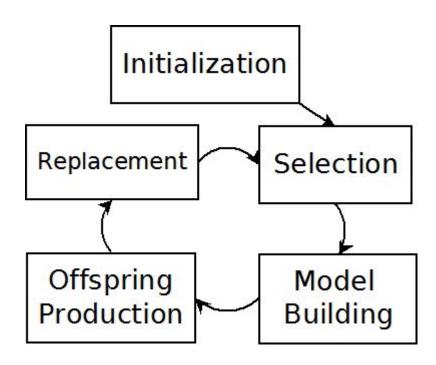
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Simple GA ⇒ Model Building GA

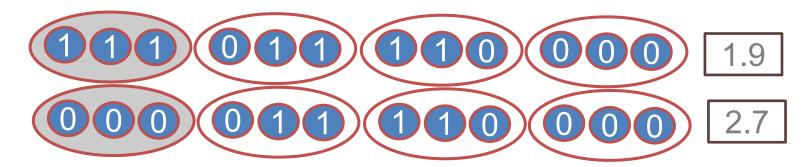
Schemata	fitness
000	0.9
001,010,100	0.45
011,101,110	0
111	1



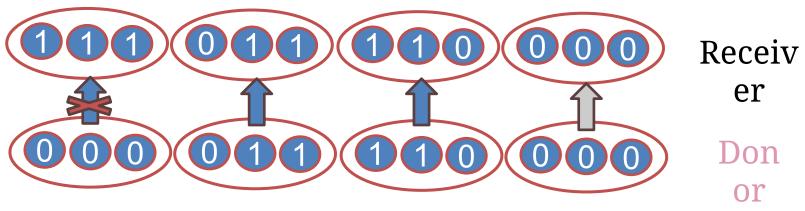


Optimal Mixing

 GA/MBGA: Large enough population ⇒ conquer sampling noise

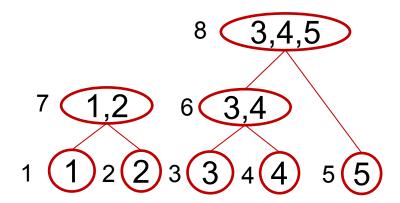


• Optimal Mixing: Donation and evaluation ⇒ noise free



Linkage Tree (LT)

- Hierarchical Clustering
- Utilized (donation) in top-down order
- Robust since it is likely to cover all BBs



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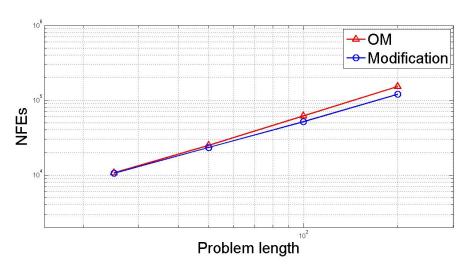
Motivational Experiment

- Small mask ⇒ find local optima
- Large Mask⇒ recombine local optima
- An experiment on trap problem with k=5

Two stage

 1^{st} generation: masks of size < 5

Other generations: masks of size ≥ 5



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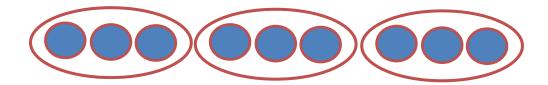
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Problem Instances

- Homogeneous separable problem
- The one-max problem



• The (m, k)- trap problem



Linkage Set

- Homogeneous and isomorphic set of masks
- Marginal product model (MP)

 $(\ell, 1)$ -MP

123456 ...

(m,k)-MP

1,2,3

4,5,6

7,8,9

• (*m*, *k*)- LT

1,2,3 4,5,6 ... 1,2 4,5 ... 1) (2) (5) (4) (5) (6)

CP Index

•
$$CP_{theo}(\mathbb{M}, P) = \frac{E[GAIN(S_{\mathbb{M}, P}, S_{\mathbb{M}, P}, \mathbb{M})]}{E[COST(S_{\mathbb{M}, P}, S_{\mathbb{M}, P}, \mathbb{M})]}$$

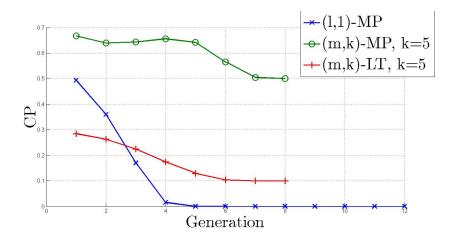
- $S_{M,P}$: random variable of schemata
- Learn distribution of $S_{M,P}$ from population

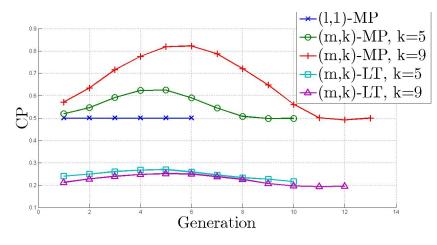
			$Cost(r, d, \mathbb{M}) = 2$
Schemata	fitness	rank	(123)
000	0.9	2	
001,010,100	0.45	1	
011,101,110	0	0	1,2
111	1	3	1 2 5

GAIN(r, d, M) = 3 - 1 = 2

Model Efficiency

Model	Pop	NFEs
	316	<u>49982</u>
	264	129300
	Fail	Fail
	188	50013
	181	45889
	137	<u>39356</u>
	188	113440
	160	91393



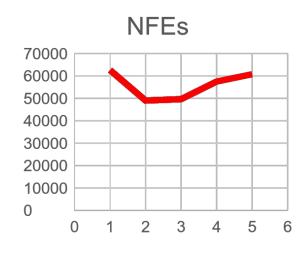


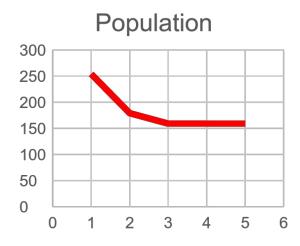
Population sizing

- Decision making ⇒ noise-free decision making
- Model building⇒ rather robust hierarchal linkage tree
- Initial supply

Population sizing

- Perform OM+LT on the (m, k)-trap problem
- Discard masks of size 1 at different generation
- Small masks in early generations and large masks in late generations





Normalized CP

•
$$CP_{theo}(\mathbb{M}, P) = \frac{E[GAIN(S_{\mathbb{M}, P}, S_{\mathbb{M}, P}, \mathbb{M})]}{E[Cost(S_{\mathbb{M}, P}, S_{\mathbb{M}, P}, \mathbb{M})]}$$

$$\bullet \quad CP_{prac}(M,P) = \frac{E[\operatorname{GAIN}(S_{M,P}^e, S_{M,P}^e, \{M\})]}{E[\operatorname{COST}(S_{M,P}^e, S_{M,P}^e, \{M\})]}$$

•
$$CP_{norm}(M, P) = \frac{CP_{prac}(M, P)}{R(S_{M,P}^e)H(S_{M,P}^e)}$$

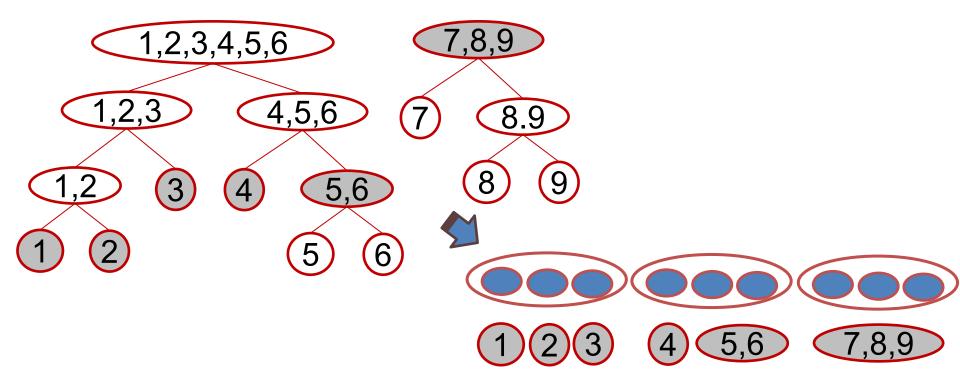
- $S_{M,P}^e$: (random variable) schemata in population
- $R(S_{M,P}^e)$: highest rank of
- $H(S_{M,P}^e)$: entropy of $S_{M,P}^e$

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Modification of OM+LT

- Stage 1, OM+ 'some masks' : $P \Rightarrow O_{meta}$, CP_{norm} info
- $CP_{norm} \Rightarrow$ 'promising masks'
- Stage 2, OM + 'promising masks' : $O_{meta} \Rightarrow O$



CP Estimation

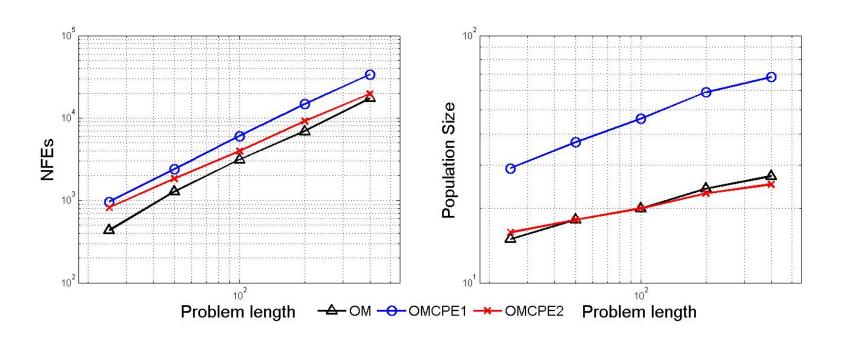
- Run OM one time, for each mask, CP= total gain/total cost
- Utilize (estimate CP) which masks for each receiver?
 Different layers for different parents
 All layers for all parents
 Parents(receivers)

1,2,3	7,8,9	1,5,9,13,17
1,2,3	4,5,6 (7) (8.9)	2,6,10,14,18
1,2 3	4 5,6 8 9	3,7,11,15,19
1 2	5 6	4,8,12,16,20

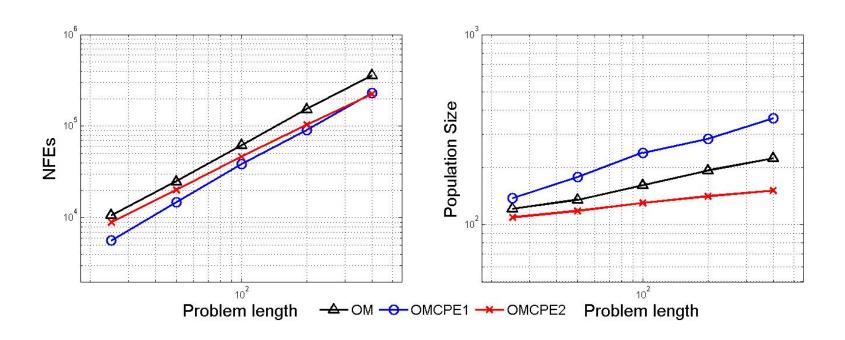
Experiment

- The one-max
- The trap problem
- The NK-landscape problem with no overlap general case of fully separable problem

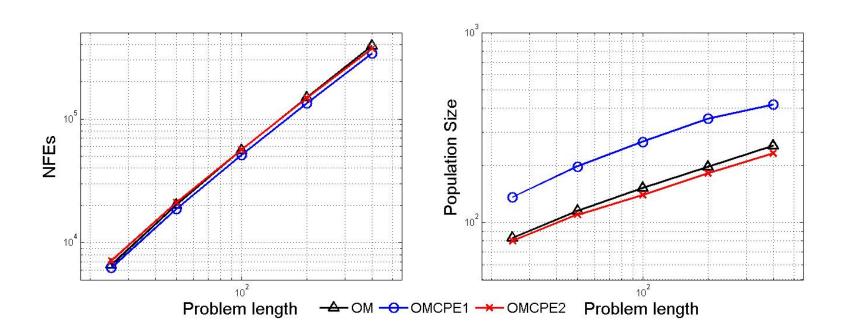
Experiment Results – One-Max



Experiment Results – Trap



Experiment Results –NK-landscape



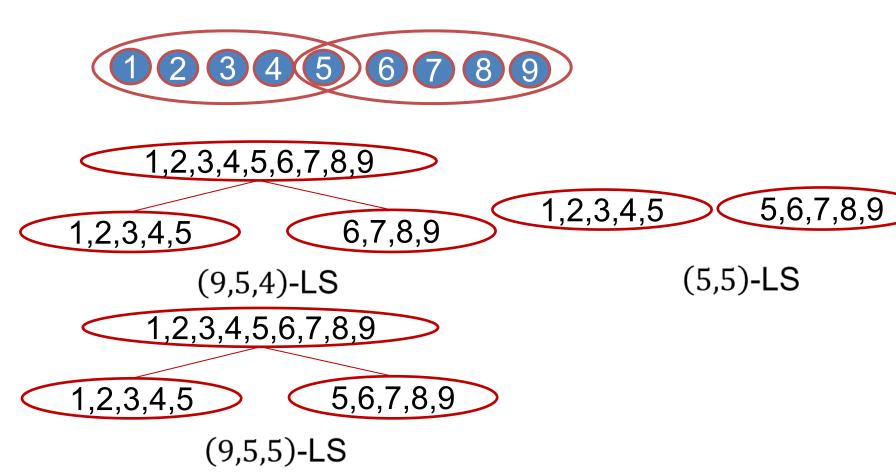
Summary & Conclusion

- OM is analyzed from the perspective of model efficiency and population sizing
- Mask pruning metric is designed
- OM-based algorithm with mask selection technique is designed
- Mask selection not only reduce NFEs but also make OM scale better
- This work can be extended to more complex scenario and help to improve OM

End

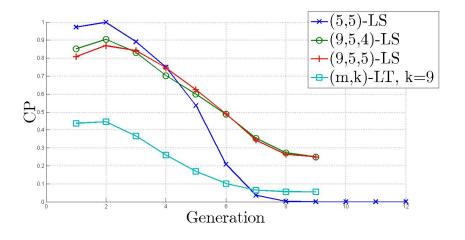
Overlap problem

The aggregate trap problem

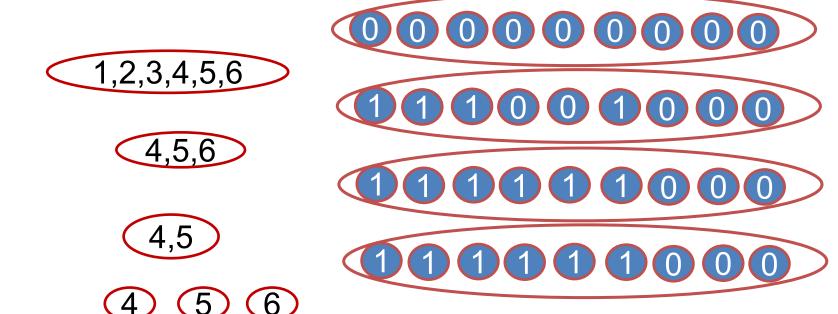


Overlap problem

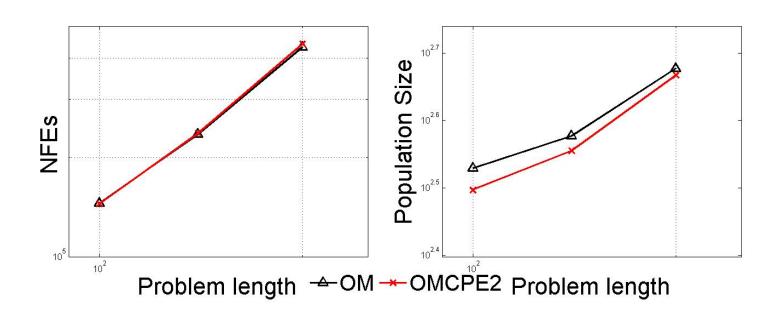
Fail
71433
68103
188352



Rank Estimation



Overlap NK-LandScape



Overlap NK-LandScape

